Chapter 6
Role of Machine Learning in Computational Fluid Dynamics

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ABSTRACT

The integration of machine learning (ML) with computational fluid dynamics

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(CFD) marks a significant advancement in the simulation and analysis of fluid flows. This chapter explores the synergistic role of machine learning in enhancing CFD methodologies, focusing on applications in modeling, optimization, and real-time analysis. Machine learning algorithms, particularly deep learning, offer powerful tools for identifying patterns and correlations within large datasets generated by CFD simulations. These algorithms can be trained to predict fluid behavior, accelerate simulation processes, and improve the accuracy of models by learning from empirical data. In modeling, ML techniques reduce the reliance on traditional empirical models, offering more precise and computationally efficient alternatives. Furthermore, ML-driven optimization techniques enhance the design process of fluid systems by enabling rapid evaluation of multiple design variables. Real-time data processing and analysis facilitated by ML also support adaptive control and decision-making in dynamic fluid environments.

INTRODUCTION

New solutions to tough problems which would have taken years and been expensive using traditional aircraft design techniques are being managed in weeks or months by means of machine learning. However, one of its most attractive potential use cases is for Computational Fluid Dynamics (CFD), a bedrock subsystem in understanding and optimising airplane designs. While traditional fluid simulations with machine learning can be used to boost the accuracy and speed of tasks which have a very different distribution from their training data (with hyper-parameter tuning, wavelet-like sensing for turbulence modelling, injection/acceleration emulation in fast-running shock physics simulators or natural convection as presented previously by improving thermal boundary layer design parameters). This chapter unveils the potential and ability of ML-powered large scale physical modelling tasks such as creating an airplane, forecasting climate reliefs. The same is true in expanded efforts, where these solutions are reaching beyond immediate predictive maintenance use cases to overflight congested areas of urban landscape inspection or remotely piloted flight controls and capabilities.